The Dark Side of CEO Networks: Evidence from Real Activities Management*

Abstract We examine the relation between CEO network size and the level of real activities management (*RAM*). Using the number of social connections to outside executives, directors, and others in similar positions to measure network size, we find that well-connected CEOs associate with higher levels of *RAM*. Social science theory suggests that this occurs because well-connected CEOs can acquire more information from their social networks to implement *RAM* effectively. The power and influence and labor market insurance from a large network also reduces the private cost of *RAM*. Supporting these two channels, we find a stronger positive relation between *RAM* and CEO network size when the CEO connects with more informed and influential persons and has more reputation to protect in the labor market. In addition, the positive relation concentrates in firms with low CEO share ownership, where a more severe misalignment of interests can occur. We also show that higher but not extreme levels of *RAM* from a large CEO network degrades the firm's long-term operating performance, suggesting that large CEO networks have a darker side for firm value.

Key Words Social networks, CEO network size, Earnings management, Real activities management.

JEL Classification G30, L14, M41.

1. Introduction

A nascent body of literature documents that executive social networks help shape firms' financial reporting policies (Bhandari et al. 2018; Ke et al. 2019; Krishnan et al. 2011).[1] These studies indicate that the social networks of executives and directors facilitate information transfer within the networks and improve corporate financial reporting practice and quality. Bhandari et al. (2018) find that CEOs with larger networks have lower levels of accrual earnings management (*AEM*)[2] and fewer financial restatements and internal control weaknesses, suggesting that social networks help well-connected CEOs improve earnings quality rather than engage in rent extraction. This literature, however, provides an incomplete assessment

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1 Gibbins et al. (1990) is perhaps the earliest mention in the accounting literature to identify social networks as potentially important for firms' accounting or disclosure decisions.

2 *AEM* refers to the purposeful altering of reported earnings by changing the methods or estimates for GAAP-based expense or revenue accruals to report earnings that differ from unmanaged earnings (Badertscher 2011).

of the relation between CEO connectedness and earnings management because it does not consider whether and how an executive social network relates to real activities management (*RAM*), a practice whereby managers purposely alter the firm's cash flow to report earnings based on departures from the timing or structuring of normal or optimal operations.

We know from prior research that a firm manager facing stricter regulation on accounting practices is more likely to use *RAM* to achieve his earnings target. *RAM*, for example, more frequently occur after the introduction of the Sarbanes-Oxley Act (SOX) of 2002, which was intended to limit questionable accounting practices (Cohen, Dey, and Lys 2008; Gilliam et al. 2015; Koh et al. 2008; Brown and Caylor 2005) and strengthen auditing standards (Cohen and Zarowin 2010; Zang 2012). We also know that the use of *RAM* tends to be limited more by the presence of institutional investors and analysts, who may discipline managers for questionable forms of *RAM*, rather than by GAAP choices (Bushee 1998; Roychowdhury 2006; Zang 2012). We do not know, however, whether *RAM* is affected by executive social network, a key factor determining costs and benefits of corporate operations as well as earnings management techniques.[3] We contend that without an analysis of *RAM*, it remains an open question as to whether CEO connectedness necessarily improves financial reporting quality by reducing *AEM*, as the prior research would lead us to conclude.

Accordingly, as our core research question, we ask whether CEO network size relates to the CEO's choice of *RAM* to manage earnings after controlling for other factors that might explain that choice. We then explore further this question by examining whether the relation between CEO network size and the choice of *RAM* varies predictably in (i) network characteristics (e.g., the amount of information sharing in the network), (ii) manager characteristics (e.g., CEO outside directorships, CEO share ownership), and (iii) firm characteristics (e.g., the level of earnings management). Lastly, we examine the related question of how *RAM* relates to the future operating performance of firms with large CEO social networks. Since prior studies show that firm managers use between *RAM* and *AEM* in a substitutional way (Badertscher 2011;

[3] Executives' social network can significantly alter firms' operating, investing, and financial policies; for example, on executive compensation (Engelberg, Gao, and Parsons, 2012), board monitoring (Fracassi and Tate, 2012), acquisition activity (El-Khatib, Fogel, and Jandik, 2015), and capital investment (Fracassi, 2016).

Cohen et al. 2008; Cohen and Zarowin 2010; Zang 2012), we control for the level of AEM throughout our analysis. It is important to note that while prior studies document the *unconditional* relation (Badertscher 2011; Cohen et al. 2008; Cohen and Zarowin 2010; Zang 2012), our study investigates whether and how CEO network size affects the use between *RAM* and *AEM*. That is, our study examines the relation between these two earnings management techniques, *conditional* on CEO network size.

We contribute to the literature by being the first to examine the relation between CEO network size and *RAM* and to identify the underlying channels through which this relation might generate benefits for or detriments to the firm and the top executive. Additionally, while the literature has been silent on whether and how *RAM* alters firm operating performance in a long-term equilibrium, our study sheds new light on the channels through which this occurs by showing that CEO connectedness is a key driver of the relation between *RAM* and firm future operating performance.

The social science literature defines a CEO's social network as a web of connections developed from past service of the CEO in executive, director, and similar positions at other firms, alumni educational network associations, and social clubs (e.g., Coleman, 1988; Brass and Burkhardt, 1992; Haunschild, 1993; Mizruchi, 1996; Mizruchi and Potts, 1998; Burt, 2000; Reagans and McEvily, 2003; Granovetter, 2005; Inkpen and Tsang, 2005). This literature identifies two main channels through which CEO network size could influence the level of *RAM*: (i) an information-sharing and communication channel and (ii) a power and influence channel, which also provides insurance against adverse outcomes in the takeover and labor markets. The first channel allows CEOs to use the information acquired from others in the network to achieve the desired level of managed earnings while minimizing the net costs (e.g., from implementation, regulatory, detection, and reputational risks). Compared to other forms of earnings management, *RAM* involves higher complexity and uncertainty (e.g., it needs to be done early in an accounting period, making it difficult to predict a precise earnings effect). Studies support the view that larger executive networks promote greater information sharing on earnings management and earnings forecasting practices (Chiu et al. 2013; Ke et al. 2019).

The second channel confers power and influence on well-connected CEOs. The implementation of *RAM* is contingent on the CEO's ability to persuade and receive support from the board to deviate from normal or optimal operating policies. This channel helps CEOs using *RAM* by insulating them from internal monitoring mechanisms (corporate governance). Fracassi and Tate (2012) show that more powerful CEOs tend to appoint directors with ties to the CEO, which weakens board monitoring and leads to more value-reducing acquisitions. Hwang and Kim (2009) find that firms with board members socially independent of the CEO compensate the CEO less and exhibit stronger pay-performance and turnover-performance sensitivity.

The second channel also helps insulate the CEO from takeover and labor-market discipline despite the potential for inferior operating performance from *RAM* in the long run. Due to its cash flow consequences, the abnormal or sub-optimal operating policies associated with *RAM* may aggravate firm future operating performance (Cohen and Zarowin 2010). However, social networks enable the executive to weather out this disciplinary role of the corporate control market. In the event of involuntary or voluntary termination, social networks may provide additional insurance to well-connected CEOs in the executive job market. Liu (2014) provides evidence that even though more centrally-located CEOs are subject to more frequent turnover, they are also more likely to land promptly an executive-level job.[4] El-Khatib et al. (2015) show that while CEOs centrally located in the social network frequently initiate value-destroying acquisitions, their previous post-merger performance is not related to both the likelihood of their firms being subsequently acquired and the likelihood of dismissal by a CEO bidder. As anecdotal evidence of the power and influence from a large network, we note that Jack Welch, General Electric's legendary former CEO, who is well-networked, is commonly known to have met or exceeded earnings benchmarks via *RAM* using mergers and acquisitions accounting as well as strategically-timed asset sales to financial institutions.[5]

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[4] Ample anecdotal evidence suggest that network or "rolodexes" play a critical role in the CEO labor market. Networks can matter for several reasons. First, a main function of managers is to bring together people and other production inputs. Managers can make extensive use of networks in the job-finding process (Burt 2000; Granovetter 2005). Second, the skills required for CEO positions can be specific across firms. The quality of candidates, their managing styles, and other personal characteristics are critical for CEO positions. In a market with high frictions, the board of directors tends to rely on social links for credible and in-depth information on a CEO candidate, as discussed by, for example, Cao et al. (2006). In addition, the connectedness of CEOs represents their social capital and outside employment opportunities. An effective compensation package would take this factor into consideration (Liu 2014).

[5] "Jack Welch was known for his fondness of business acquisitions. 'Accretive' means that a merger per se can instantly push up E.P.S. if, percentage-wise, the earnings added to the acquirer's books are larger than the additional stock the acquiring firm must issue as part of the merger (if any). This trick works even if subsequently slower growth in the acquired firm's earnings drags down the overall growth of E.P.S. of the combined entities. Remarkably, most

It is *a priori* not certain whether CEO network size increases or decreases *RAM*. On the one hand, network size can improve financial reporting quality by using information extracted from the network. CEOs with a larger social network could acquire value-relevant information via their personal and professional connections and have a better comprehension of how uncertain and volatile business environments affect their firm's cost structure and product demand and supply. The social network should enable them to respond more efficiently to future shocks to their operating environments. Thus, we predict that well-connected CEOs will *less likely* to deviate from their firm's normal or optimal operating polices and engage in *RAM* (or perhaps not at all) along with lower levels of *AEM*.

On the other hand, well-connected CEOs could choose *RAM* over *AEM* as the costs and risks of *AEM* are expected to exceed those of *RAM*. As noted above, both forms of earnings management practices can misstate underlying firm performance yet impose different costs and risks on the well-connected CEO. With *AEM*, while the practice may not always be opportunistic or intentional, a large discretionary accrual can be costly to firm stakeholders and managers because its detection raises questions about a possible violation of the use of GAAP.[6] Once detected, *AEM* can also induce harmful effects on well-connected CEOs' reputation in their social network and outside options from questionable or potentially unlawful actions.

By contrast, *RAM* adjustments can be less detectable and less costly, and may not raise the same level of scrutiny about appropriate GAAP (Cohen, Dey, and Lys, 2008; Cohen and Zarowin, 2010). Even though *RAM* can exacerbate the inefficiency of corporate cash reserves, well-connected CEOs derive power and influence as well as executive labor market insurance via their social network, which further lowers the

financial analysts in the 1990s fell for this trick and bid up its P/E ratio even higher." (Uwe Reinhardt, *New York Times*, February 13, 2009).

[6] *AEM* detection, moreover, can significantly affect firm stakeholders if it results in a Securities and Exchange Commission (SEC) inquiry, a restatement, or securities litigation (Bruns and Merchant, 1990; DuCharme, Malatesta, and Sefcik, 2004; Graham, Harvey, and Rajgopal, 2005; Gong, Louis, and Sun, 2008; Zhang, 2012). For example, DuCharme et al. (2004) show that abnormal accruals are highest for firms with seasoned equity offerings (SEO) that are subsequently sued. Settlement amounts are also positively related to the levels of abnormal accruals. Gong et al. (2008) show a positive association between stock-for-stock acquirers' pre-merger abnormal accruals and post-merger announcement lawsuits. CEOs with a large network could find litigation resulting from accrual manipulation particularly costly because the litigation and penalization tarnishes well-networked CEOs' reputation, jeopardizing their outside options in the executive labor market. Also, *AEM* is constrained by outside monitoring and GAAP rules, making it harder to convince auditors of managers' earnings management choices (Zang 2012).

expected cost of *RAM*. Thus, CEOs with large networks may engage more actively in higher levels of *RAM*. Thus, it is an empirical question whether CEO network size is positively or negatively correlated witth *RAM*.

To test these predictions, we first construct the CEO's social network for a sample of U.S. firms by extracting those CEO's professional, educational, and social connections from BoardEx (Engelberg et al. 2013). As detailed in Section 4, for network size, we use a measure of CEO connectedness, calculated as the sum of direct connections to outside executives or directors linked to the CEO through the executive's past or current business relationships, affiliations with charitable or volunteer organizations, past or current service on boards, and past tertiary schools attended. Second, we follow the earnings management literature and combine measures of the abnormal level of operating cash flow, production cost, or discretionary expenditure to proxy for *RAM*. This literature shows that this *RAM* proxy (and related *AEM* proxies) associates with financial reporting behavior in a wide range of settings.[7] The use of a *RAM* proxy also avoids a look-ahead bias, which can occur when a researcher uses an ex-post variable (e.g., an SEC enforcement action, a restatement, a securities class action lawsuit) to infer earlier financial reporting behavior.[8] We measure all variables at the firm/CEO level annually and analyze a maximum sample of 24,549 firm-years and 4,362 unique firms over 1999–2014.

We document four key findings. First, we find a *positive* relation between CEO network size and the level of *RAM*, which is both statistically significant and economically meaningful. The average level of *RAM* increases by around four to five percent for every one thousand additional connections. This finding

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7 Representative studies include (i) why and when some firms are more likely to engage in earnings management (Badertscher 2011; Chan et al. 2015; Cohen et al. 2008; Ewert and Wagenhofer 2005; Roychowdhury 2006; Zang 2012), (ii) whether equity incentives matter (Armstrong et al. 2010; Bergstresser and Philippon 2006; Cheng and Warfield 2005), and (iii) the effects of detected earnings management on performance (Cohen and Zarowin 2010; Gunny 2010), capital costs (Aboody et al. 2005; Francis et al. 2004; Kim and Sohn 2013), debt covenants (DeFond and Jiambalvo 1994), and firm value (Bartov et al. 2002; Kasznik and McNichols 2002; Myers et al. 2007). Forms of earnings management around different events and in different settings have also been explored. Examples include (i) share offerings (Kothari et al. 2005; Teoh et al. 1998), (ii) regulatory changes (Cahan et al. 1997; Cohen et al. 2008),(iii) management turnover (Desai et al. 2006; Guan et al. 2005; Hazarika et al. 2012; Wells 2002), (iv) restatements (Ettredge et al. 2010; Richardson et al. 2002), (v) litigation events (Dechow et al. 1996; DuCharme et al. 2004), and (vi) bad debts (McNichols and Wilson 1988). See Xu et al. (2007) for a review of the pre-2007 *RAM* literature.

8 Nonetheless, we test our results using a restatement sample to provide a more complete picture with respect to the effect of CEO network size on earnings management (Section 5.4.1). We acknowledge that these proxies represent noisy estimates of the earnings adjustment by a CEO or other senior officer to meet a benchmark.

supports the prediction that larger CEO social networks associate with higher levels of *RAM*. The positive relation between CEO network size and the level of *RAM* also persists after we control for the level of *AEM* and when we use alternative network and *RAM* measures, different time periods, and a two-stage instrumental-variable approach.

Second, we find a stronger positive effect of CEO network size on the level of *RAM* for networks that are more informative or influential, consistent with the two channels through which networks could increase *RAM*. Specifically, we find a stronger positive relation between *RAM* and CEO network size for connections to executive directors who are directly involved in the firm's operating activities versus indirectly involved non-executive (outside) directors, and connections to individuals in S&P 500 firms, which are large and reputable compared to others. We consider these connections as conducive to higher levels of *RAM* because they increase information access, exert more influence, and create higher-level employment opportunities. We also find evidence of a contagion effect, that is, the level of *RAM* by the focal firm associates positively with the average level of *RAM* of connected firms, supporting the idea that information on *RAM* practices is transmitted through CEO social connections.

Third, we find that high levels of *RAM* presage poorer return on assets and lower operating cash flow when the CEO network is large. By contrast, we do not find a negative association between *RAM* and future operating performance when the CEO network is small. Thus, while engaging in *RAM* per se may not necessarily be value-decreasing for a firm,[9] larger networks apparently embolden the CEO to deviate from optimal operational decision-making to the extent that the costs exceed the benefits to the firm. Consistent with Gunny (2010), we find that the negative effect on future operating performance of high levels of *RAM* is attenuated if well-connected CEOs undertake *RAM* just to meet or beat earnings benchmarks. In other words, up to a moderate level of *RAM*, the choice of *RAM* is firm-wise desirable to the extent that the net benefits from delivering superior earnings to the market exceed the costs of sub-optimal operational

[9] Gunny (2010) finds that firms use *RAM* to more successfully meet or beat a benchmark and have better future operating performance. Taylor and Xu (2010) find an insignificant difference in the future operating performance of *RAM* firms and non-*RAM* firms.

decision-making. At an aggressive level, however, the CEO's preference for *RAM* could be a symptom of misaligned incentives leading to poor operating performance.[10]

This third finding suggests a dark side of CEO social networks, in that well-connected CEOs could reap more private gain from an aggressive level of *RAM* to the detriment of long-term firm performance. Meanwhile, CEOs who acquire significant power and influence through their social networks are more resistant to internal and external monitoring and discipline. This permits them to extract benefits from high levels of *RAM* while bearing few private costs, which leads to firm-wise undesirable and value-decreasing operational decision-making. Consistent with this interpretation, we find that the positive relation between CEO network size and the level of *RAM* and the negative relation between *RAM* and future operating performance concentrates in the subsample with low CEO share ownership, where the misalignment of interests is most severe.

Finally, we document that CEO network size relates negatively to the level of *AEM* and to the possibility of a future restatement. CEOs with larger networks should also be less inclined to engage in aggressive *AEM* because they could suffer greatly from a reputation loss resulting from a reported GAAP departure or class action litigation. When we regress proxies for *AEM* on CEO network size and control variables (including *RAM*), we find that the coefficient for network size is negative, indicating that well-connected CEOs are less likely to use high levels of *AEM* controlling for the level of *RAM*. These accrual and restatement results confirm the findings in Bhandari et al. (2018). However, the conclusion differs from Bhandari et al. (2018). We contend that while prior research suggests that larger CEO networks improve financial reporting quality through a reduction in *AEM*, our study indicates that well-connected CEOs use a different earnings management technique, or RAM, to achieve their private gains. As such, our study offers a more complete portrayal of the relation between CEO connectedness and earnings management by examining whether the relation between *RAM* and network size goes beyond what a substitutional relation

[10] The private gains to executives from potential short-term stock appreciation after *RAM* include increased compensation, more outside employment options, and enhanced reputation, which could be amplified for well-connected CEOs (Engelberg et al. 2013; Liu 2014). Despite research showing that *RAM* imposes capital costs (Kim and Sohn 2013) and may worsen future firm performance (Leggett et al. 2009), a well-connected CEO who justifies these activities to the board and other outside powerful executives, and who has access to outside employment opportunities, may have less concern for these longer-term costs to the firm.

between *AEM* and *RAM* might explain (Badertscher 2011; Cohen et al. 2008; Cohen and Zarowin 2010; Zang 2012). Thus, executive social networks play a *different* role in explaining CEOs' use of *RAM* as opposed to *AEM* as an earnings management practice.

Our paper proceeds as follows. Section 2 states the hypotheses. Section 3 describes the sample and data. Section 4 outlines the research design. Section 5 presents the results, and Section 6 concludes.

2. Hypothesis Development

We combine two strands of literature to develop our hypotheses. We first rely on the social science literature to define a CEO's social network as the number of ties the CEO has to other CEOs and senior executives through shared professional, educational, and social experiences. This literature suggests that a large network benefits CEOs through two key channels: (i) better access to relevant information internal and external to the firm and (ii) higher reputation and greater power and influence (Brass and Burkhardt 1992; Burt 2000; Coleman 1988; Granovetter 2005; Haunschild 1993; Inkpen and Tsang 2005; Mizruchi 1996; Mizruchi and Potts 1998; Reagans and McEvily 2003). Higher power and influence can also provide insurance against adverse outcomes in the takeover and executive labor markets (El-Khatib et al. 2015; Liu 2014).[11]

In the context of *RAM* adjustments, a CEO's social network may be either beneficial or harmful to the firm and shareholders. Shared information, for example, may allow network members to improve decision making and establish acceptable and (privately) beneficial practices by relying on the information of others. More specifically, shared information from the CEO social network may allow executives to choose low levels of *RAM* so as not to deviate noticeably from their firm's optimal operating policies. In this situation, we predict that they will engage more actively in lower levels of *RAM* (or perhaps not at all) after weighing the costs and benefits of these two earnings management practices. In related research, Ke et al. (2019) show that CEOs with connections to other top executives within the same firm produce more accurate

[11] These two network traits are not separate and distinct, however. Nonetheless, observing the different responses of well-connected CEOs to *RAM* decisions (e.g., the effects of *RAM* on future operating performance) may shed light on which trait dominates in explaining how CEO networks relate to financial reporting.

management guidance forecasts.[12] However, we also note that dysfunctional information is also shared among the social network members. *AEM* practices are shared among interlocked board members (Chiu et al. 2013). Bizjak et al. (2009) show that the practice of backdating employee stock options spreads from firm to firm through networks of shared directors.

With the second channel, well-connected CEOs seek to increase their private interests of wealth and reputation by exploiting their power and influence to insulate themselves from internal monitoring by the board and external discipline by the executive labor market (Bebchuk et al. 2011; Fracassi and Tate 2012; Hwang and Kim 2009; Masulis et al. 2007). Less effective monitoring from larger social ties also influences corporate operating activities. Ishii and Xuan (2014) find that social ties between the bidder and target lead to value losses, potentially because social conformity weakens critical analysis and due diligence. Chikh and Filbien (2011) show that well-connected CEOs continue to support acquisitions even if the market reacts negatively upon announcement. Well-connected CEOs could also use *RAM* to increase their personal wealth and reputation, although this would be at the expense of shareholder value in the long run. However, the private interests of wealth and reputation of well-connected CEOs with a high ownership stake in the firm could also align well with outside shareholders' interests, which may curtail their use of *RAM*.

Because the preceding discussion, we state our first hypothesis in the alternative form as follows.

H1: A firm's earnings adjustments from *RAM* vary positively in CEO network size.

To improve our identification strategy that *RAM* might causally relate to network size, we test cross-sectionally whether certain CEO networks, particularly those with more powerful and influential members in the network, associate with a higher level of *RAM* than others. We, thus, conduct tests of whether *H1* holds when the network includes more connections to people of power and influence and those who are also likely to share higher-quality information through the network. Below, we discuss two proxies for

[12] See, also, Glaeser et al. (1992) and Jaffe et al. (1993). CEO networks also flourish as business organizations that actively promote membership based on information sharing, where CEO members can share ideas, best practices, and experiences in a confidential and conflict-of-interest free environment (www.chiefexecutivenetwork.com).

these factors, whether (i) BoardEx uses the classification of executive director or non-executive director and (ii) the network connections involve CEOs at large firms.

First, executive directors participate in daily corporate operations and have greater direct knowledge, reputation, and power to influence decision-making. Connections to executive directors should, thus, provide a given CEO with power and influence as well as better information. In contrast, theoretical models describe non-executive directors (such as outside directors) as advisors who rely on executive directors to provide proprietary information to them (Adams and Ferreira 2007). Thus, their information quality is lower than that of executive directors (Ravina and Sapienza 2010). Second, ties to larger firms are more likely to deliver competitive advantage and reputation to a given CEO compared to ties to CEOs at smaller firms. Firms with a higher market share are also a better source of high-quality information as well as an attractive coalition. Conversely, a firm's size may be merely an outcome of past successful business policies and strategies and information that allow for market penetration. Overall, the effects of deriving power and influence from executive social networks and their insurance benefits in the labor and takeover markets should be stronger for CEOs with powerful and influential connections. Our second hypothesis is as follows.

H2: The positive relation between CEO network size and *RAM* strengthens for networks with people of power and influence.

Third, we consider whether firms that manage earnings with *RAM* fare better or worse in the future than those that do not (and may also have missed their earnings targets). Firms that engage in *RAM* may do worse because the outcomes to generate the earnings adjustments arise from the inefficient use of cash. The evidence on this point is mixed. Gunny (2010) finds that firms conducting *RAM* to meet or beat a benchmark have better future operating performance; Taylor and Xu (2010) find that *RAM* firms do not differ in future operating performance compared to non-*RAM* firms; and Leggett et al. (2009) find that *RAM* firms have worse future operating performance. These studies, however, do not investigate whether CEO network size conditions the relation between *RAM* and future operating performance. For one, using shared information as well as power and influence channels, well-connected CEOs may exploit *RAM* to achieve private gains at the expense of firm value. In that case, we predict a negative association between *RAM* and future firm performance for CEOs with larger social networks.[13] On the other hand, well-connected CEOs may use *RAM* to motivate firm performance, signal firm value, and build reputation (Bartov et al. 2002; Burgstahler and Dichev 1997; Subramanyam 1996). This view suggests that CEOs extract relevant information through their information channels to further optimize their decisions on *RAM*. Under this scenario, we expect a positive correlation between *RAM* and future firm performance for CEOs with large social networks. We examine the relation among *RAM*, future operating performance, and CEO network size by testing the following (non-directional) hypothesis.

> *H3*: The relation between future operating performance and a firm's earnings adjustments from *RAM* is conditional upon the size of the CEO's network.

3. Sample and Data

We start with the BoardEx database (http://corp.boardex.com/data/), which contains biographical information on the senior executives and board members of public and private firms. A November 2015 BoardEx report provides a summary of board composition and senior management team by year (from January 1999 to November 2015) for 12,972 companies in North America. For each director or executive, BoardEx compiles a full historical profile containing the past employment history, current employment, board memberships, educational background, and social activities such as memberships in social and charitable organizations. BoardEx states that they gather and verify information from multiple reliable sources and build profiles as complete as disclosure allows.

We next extract firm-level financial and accounting information from Standard & Poor's Compustat North America and then merge BoardEx with Compustat by linking the BoardEx firm identifier (CompanyID) to the Compustat identifier (GVKEY). BoardEx provides the International Securities Identification Number (ISIN) for firms with stock quotes. We then extract CUSIP from ISIN and match it to the GVKEY Compustat header. We are able to find the GVKEY for 7,433 quoted firms in BoardEx through this matching process. For the BoardEx firms without ISIN, we use a Levenshtein algorithm

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[13] We also refine this prediction by examining whether the negative association between *RAM* and future firm performance for CEOs with larger social networks is attenuated when the CEO holds a larger ownership in the firm, which should better align the CEO's private interests with outside shareholders' interests.

(http://www.keldysh.ru/departments/dpt_10/lev.html) to aid in approximate name matching and verify the matched pairs manually. We are able to find the GVKEY for an additional 1,007 BoardEx quoted firms under this procedure. In total, we find the GVKEY for 8,440 out of 8,558 (98.6%) quoted U.S. firms covered by BoardEx. The remaining 118 firms are either too small or too new for Compustat coverage. We obtain stock return information from the Center for Research in Security Prices (CRSP). Using the link history table of CRSP/Compustat Merged (CCM) dataset, we merge BoardEx and Compustat fundamentals data with CRSP stock return data. To identify a unique CRSP security identifier (PERMNO) for each firm-year observation, we ensure that the fiscal year end date is within the effective link dates and choose the link with the CCM primary security marker and primary link type marker.

Table 1 summarizes the 24,549 observation sample by fiscal year and industry classification and shows a broad sample of unregulated, non-financial firms, covering approximately 66 and 74 percent of CRSP stocks at the beginning and end of the sample period, respectively. Differences in accounting and reporting and industry regulation oblige us to exclude firms in the financial (SIC 6000-7000) and the utility industries (SIC 4400-5000). While the most represented industries are business services (15.53%), electronic equipment (9.69%), and petroleum and natural gas (7.40%), each of the other 39 industries represents less than seven percent of the sample. The larger coverage of firms in BoardEx is constrained by the requirement for earnings management measures computed from Compustat data. Note, also, that the connections forming a CEO's network derive from links among all organizations in BoardEx biographical histories, not just among the sample firms.

4. Research Design

4.1 CEO Network Size Measure

We measure CEO network size annually as the number of executives or directors in the network with whom the CEO has connections. We define a CEO network connection at year *t* as one established between a CEO and another individual if they link on one or more of employment, education, or other activities (e.g., social club) during or prior to year *t*. Two individuals are connected via employment if their careers overlap with the same employer in the same year. We exclude any connections the CEO has with other individuals currently employed at the same firm.

Individuals are connected via education if they have graduated within a year from the same university and have the same degree type. Education overlaps are identified based on BoardEx education file. Following Cohen et al. (2008), we clean the BoardEx education file in two ways. First, for universities with multiple Institute IDs, we aggregate them into a single Institute ID. For example, BoardEx assigns "Stanford University" ID # 743905436, "Stanford University, Graduate School of Business" ID # 8034910975, "Stanford University School of Law" ID # 9164011235, and "Stanford Medical School" ID # 5881139024. We merge all of these into the "Stanford University" ID. Universities with an unspecified campus are assumed to be the flagship campus. Second, BoardEx does not list a unique ID for degree type, only a description of the executive's "qualification." We map each of the degree descriptions into (i) undergraduate, (ii) masters, (iii) MBA, (iv) Ph.D., (v) law, (vi) medical, and (vii) other education. We drop professional certificates such as CFA or CPA designations.

Two individuals are connected via other social activities if they both have active roles in the same professional/non-profit association or social club. Following Engelberg et al. (2013), we require that both individuals' roles exceed mere membership, with the exception of social clubs. We do not require the roles to overlap in time, however, because most have missing start and end dates for social activities.

Our measure of network size for firm i's CEO sums these direct connections for each year *t* as follows: $NETWORK\_TOT_{i,t} = \Sigma Network\_Employment_{i,t} + \Sigma Network\_Education_{i,t} + \Sigma Network\_Activity_{ii,t}$ where *Network_Employment* sums the CEO's employment connections, *Network_Education* sums the CEO's education connections, and *Network_Activity* sums the CEO's other-activity connections.[14] Table 2 shows summary statistics for network size (*NETWORK_TOT*) (in thousands). The average CEO in our sample has 145 connections with a standard deviation of 197 connections and a median CEO in our sample has 61 connections. Similar to Fracassi and Tate (2012) and Engelberg et al. (2013), these data skew to the right.[15]

[14] Our measure of network, based on the sum of a CEO's direct connections, is often referred to as the "*Absolute Degree*" measure of network connectedness. Other measures of connectedness represent the "*Betweenness*", "*Closeness*", "*Eigenvector*", and "*Relative Degree*" dimensions of network connections. For completeness, we report the results of estimating Eq. (5) for each of these other measures. Table 13 reports the results.

[15] As a robustness check, we also specify the natural logarithm of CEO network size as the experimental variable and find results qualitatively the same as those reported in Table 4.

4.2 Real Activities Management Measure

Following prior work (Cohen et al. 2008; Roychowdhury 2006), we proxy for *RAM* by combining estimates of the abnormal level of operating cash flow, production cost, and R&D expenditure. First, for each firm-year, abnormal operating cash flow equals actual cash flow from operations (CFO) less normal CFO defined by Eq. (1) below.

$$CFO_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta_1\left(S_{it}/AT_{it-1}\right) + \beta_2\left(\Delta S_{it}/AT_{it-1}\right) + \varepsilon_{it}, \quad (1)$$

where CFO_{it}= operating cash flow in year *t* of firm *i*, AT_{it-1}= lagged total assets, S_{it}= Net sales in year *t* of firm *i*, and ΔS_{it}= change in net sales from the prior year.

Second, abnormal production cost equals actual production cost less normal production cost defined by Eq. (2) below as a linear function of the cost of goods sold and the change in inventory.

$$PROD_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta_1\left(S_{it}/AT_{it-1}\right) + \beta_2\left(\Delta S_{it}/AT_{it-1}\right) + \beta_3\left(\Delta S_{it-1}/AT_{it-1}\right) + \varepsilon_{it}, \quad (2)$$

where $PROD_{it}$ = $COGS_{it}$ + ΔINV_{it}, $COGS_{it}$ = cost of goods sold in year *t* of firm *i*, ΔINV_{it}= change in inventory in year *t* of firm *i*, and the other variables are defined as before. Abnormal production cost is the difference between actual production cost and normal production cost.

Third, abnormal discretionary expenditure equals actual discretionary expenditure less normal R&D defined by Eq. (3) below.

$$DISEXP_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \beta\left(S_{it-1}/AT_{it-1}\right) + \varepsilon_{it}, \quad (3)$$

where actual $DISEXP_{it}$= discretionary expenses in year *t* for firm *i* calculated as the sum of research and development, advertising, and sales, general, and administrative expenses.

Following Cohen et al. (2008), we combine the three abnormal *RAM* measures to capture the effects of real activities management as a single measure and define RAM_{it} = (CF_RAM_{it} – $PROD\_RAM_{it}$ + $DISEXP\_RAM_{it}$) times -1. We multiply the summation by -1 so that a higher value represents additional *RAM* earnings from these activities.

4.3 Descriptive Statistics

Table 2 lists the descriptive statistics. The average firm reflects a *RAM* adjustment of -2.5 percent of total assets with a median level of 2.7 percent. Thus, on balance, more of the firm-years have positive measures of our proxy for *RAM* earnings management, that is, reported earnings are more-likely-than-not higher due to *RAM*. While *RAM* is skewed to the left, we also observe that the approximately equivalent Q1 and Q3 quartiles suggest a broadly symmetric distribution around the median value. The balance of the variables in Table 2 describes the distribution of the variables in regressions of *RAM* on network size and control variables. Most of the variables reflect distributions similar to those that describe any large and diversified sample of listed U.S. firms. For example, 74.5 percent are audited by a Big 4 accounting firm, a large majority reflect positive past sales growth (*SALES_GROWTH*) and future growth opportunities (*BTM*), and the log of market capitalization (*SIZE*) is reasonably symmetric around the mean of 6.192 (or $489 million). We also calculate a proxy for *AEM*, based on the modified Jones (1991) model.[16] Mean *AEM* for the sample is close to zero and ranges between minus 5 and plus 5 percent of total assets for the majority of firms in the sample.

4.4 Regression Models

To capture the effect of CEO network size on real activities management, we regress *RAM* on *NETWORK_TOT* and controls, shown below as Eq. (4). We measure all variables on a firm-year basis. The equation is:[17]

$$RAM_t = \beta_1 NETWORK\_TOT_t + \beta_2 AEM + \beta_3 SIZE + \beta_4 BTM + \beta_5 ROA + \beta_6 LEV + \beta_7 EVOL + \beta_8 CFVOL + \beta_9 CYCLE + \beta_{10} SALES\_GROWTH + \beta_{11} MKT\_SHARE + \beta_{12} ZSCORE + \beta_{13} NOA + \beta_{14} INSTOWN + \beta_{15} CEO\_AGE + \beta_{16} CEO\_TENURE + \varepsilon_t \quad (4)$$

We measure the variable of interest, *NETWORK_TOT*, as the summation of the CEO's employment, education, and other activity connections. Eq. (4) also includes controls to isolate the CEO network effects from other firm- and manager-related characteristics. We also add *AEM* as a control, so that the coefficients for *NETWORK_TOT* capture the response of *RAM* to network size incremental to the ability of *AEM* to

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16 We define *AEM* as follows.

$$TA_{it}/AT_{it-1} = \alpha_0 + \alpha_1\left(1/AT_{it-1}\right) + \alpha_2\left((\Delta REV_{it} - \Delta REC_{it})/AT_{it-1}\right) + \alpha_3\left(PPE_{it}/AT_{it-1}\right) + \alpha_3\left(IBXI_{it-1}/AT_{it-1}\right) + \varepsilon_{it},$$

where: TA_{it}= total accruals for a firm *i* in year *t*, ΔREV_{it}= change in net revenue in year *t-1* to *t*, ΔREC_{it}= change in net receivables, PPE_{it}= gross property, plant, and equipment, $IBXI_{it-1}$= income before extraordinary items at year *t-1*, and AT_{it-1}= lagged total assets. We estimate the above regression cross-sectionally for all industry-years with at least 15 observations. We then define the estimated residuals as the proxy for accrual-based earnings management, that is, $AEM_{it} = TA_{it}/AT_{it-1}$ – estimated (TA_{it}/AT_{it-1}).

17 Intercept terms are estimated but not reported for brevity.

explain *RAM*. To control for scale effects and profitability, we include firm size (*SIZE*), return on assets (*ROA*), financial leverage (*LEV*), and book-to-market ratio (*BTM*) (Cohen et al. 2008; Kothari et al. 2005; Roychowdhury 2006). We also control for earnings volatility (*EVOL*) and cash flow volatility (*CFVOL*), as some firms may manage volatile performance. To control for the cost associated with real activities management, we include sales growth ratio (*SALES_GROWTH*), market share (*MKT_SHARE*) and financial health (*ZSCORE*) (Chan et al. 2015; Zang 2012). We also include institutional ownership percentage (*INSTOWN*) as a control because firms with lower institutional holdings may be more inclined to cater to retail investors with less awareness of the mechanics of *RAM*. In addition, we include CEO age (*CEO_AGE*) and the number of years that the CEO has held the position (*CEO_TENURE*) to control for CEO characteristics (Ali and Zhang 2015; Liu 2014). Lastly, we include year- and industry-fixed effects and report *t*-statistics with standard errors adjusted for clustering by industry (since firms in the same industry share common factors) and year (since the same CEO may enter in multiple years).

5. Results

We present our results in four sections. The first (Section 5.1) examines Eq. (4), which regresses the level of *RAM* on CEO network size and control variables (*H1*). We then address several endogeneity concerns related to CEO network size. We also summarize various robustness tests of the main results from this analysis. Our second set of results (Section 5.2) examines whether the network relation in Eq. (4) is especially strong when the connections are informative or influential. Specifically, we examine hypotheses about whether *H1* differs for CEOs with more ties to executives in high level positions, who work at larger firms, and whose choice of *RAM* relates to its use by other firms (*H2*). A third section (5.3), examines the possibility that CEO networks have a darker side by testing hypotheses about the relation between *RAM* and the firm's future operating performance conditional on network size (*H3*). A fourth section (5.4) examines whether the network effect on *RAM* differs from earnings management measures based on restatements and accruals.

5.1 CEO Network Size and the Level of RAM

5.1.1 Baseline Result

Columns 1 and 2 of Table 3 report the main finding of regressing *RAM* on network size and control variables based on ordinary least squares (OLS) regression. The variable of interest in Table 3 is *NETWORK_TOT*, which shows a significantly positive coefficient ($p<0.01$) in both OLS regressions.[18] Thus, the level of *RAM* to increase earnings varies positively in CEO network size. This supports *H1*. As the underlying mechanism for this result, we contend that larger CEO networks encourage larger *RAM*, at least from the CEO's perspective, because the larger network lowers the net cost of the activity to the CEO, either through channels that share information (by lowering detection probability or regulatory and labor market costs conditional on detection) or through power and influence channels that enhance reputation (e.g., by delivering superior earnings to the market). Based on the *RAM* coefficient in columns 1 and 2 of Table 3, assuming a relevant range of linearity, one thousand additional social connections increases the average level of *RAM* by 3.88 to 4.65 percent.

We also observe that several of the control variables, namely, *AEM*, *SIZE*, *BTM*, *LEV*, *CFVOL*, *ZSCORE*, and *NOA* significantly explain *RAM* at $p<0.01$. Thus, absent network effects, firms using higher levels of *RAM* are smaller (*SIZE*), less risky (lower *ZSCORE* and *CFVOL*), more leveraged (higher *LEV*) and have higher future growth opportunities (*BTM*). *CYCLE* and *NOA* are also significant, suggesting that higher *RAM* firms have a longer business cycle (*CYCLE*) and operating (*NOA*) assets. Also, the positive and significant coefficients on *AEM* indicate that firms use in a complementary way the two different earnings management practices such as *RAM* and *AEM*. Column 2 of Table 3 also indicates that older CEOs or CEOs early in their tenure have higher *RAM*.

5.1.2 Endogeneity and Related Issues

While we have specified models with CEO network size as an exogenous determinant of *RAM*, the positive association between CEO network size and the level of *RAM* could be subject to endogeneity and selection bias. We use several remedies to address these issues. We first consider the possibility that an

[18] We also obtain similar significant results ($p<0.01$) when we scale *NETWORK_TOT* by total network size for each year, indicating that our results are robust to alternative econometric methods or year effects.

improvement in accounting performance from *RAM* could boost the CEO's visibility and induce an increase in network size. As a simple way to alleviate this potential for reverse causality, we lag *NETWORK_TOT* by one year and find a similar positive relation between CEO network size and *RAM*. Further, we use an instrumental variable for CEO network size, *DIR_SUPPLY100*, which is the number of executives and directors of other firms in the same industry (based on two-digit SIC codes) within 100 miles of the firm's headquarters. We contend that the geographical proximity to other executives is likely to be positively associated with the connectedness of the CEO but is unlikely to result from a higher level of *RAM.* While the *RAM* conducted by CEOs could induce better short-term performance and enhance their visibility and connectedness, *RAM* is unlikely to attract other executives to relocate in the same area.

This instrumental variable approach also helps address selection bias, that is, the expectation of beneficial *RAM* could prompt a CEO to intentionally build stronger networks to maximize the benefits. For example, CEOs who contemplate using *RAM* could choose to become involved in a social organization or serve as an outside board member for a public company. The instrumental variable based on geographic location is immune to this alternative interpretation because CEOs may have little control over where the firm is located. Even if they do, they are unlikely to relocate to a firm just for the purpose of conducting a certain accounting practice.

A more general endogeneity issue relates to omitted variables. Perhaps network size is correlated with some unobservable CEO characteristic that causes a high level of *RAM*. A suitable instrument in our context would be a variable that affects the CEO network (relevance condition) and affects *RAM* only through its effect on CEO network (exclusion condition). Geographic distance has been shown to affect accounting practices through social networks in prior research. For example, Choi et al. (2012) suggest that geographic proximity between auditors and firms enhance audit quality because they may "have informal interactions in business or social settings, allowing for more information to be passed between individuals." Similarly, we contend that CEOs close to many other executives and directors are more likely to have a large network, and hence better information and power and influence to conduct *RAM*. The instrument meets the exclusion condition to the extent there is no other reasonable channel linking the location of the firm's headquarters to the use of *RAM*.[19]

To strengthen our prediction that *NETWORK_TOT* relates to *DIR_SUPPLY100* incremental to industry effects, we also include average network size for the *other* firms in the dataset in the same industry of firm *i* in year *t* (*IND_NETWORK*) as an additional instrumental variable. We estimate the following equation.

$$NETWORK\_TOT_t = \beta_1 DIR\_SUPPLY100 + \beta_2 IND\_NETWORK + \beta_3 AEM + \beta_4 SIZE + \beta_5 BTM + \beta_6 ROA + \beta_7 LEV + \beta_8 EVOL + \beta_9 CFVOL + \beta_{10} CYCLE + \beta_{11} SALES\_GROWTH + \beta_{12} MKT\_SHARE + \beta_{13} ZSCORE + \beta_{14} NOA + \beta_{15} INSTOWN + \beta_{16} CEO\_AGE + \beta_{17} CEO\_TENURE + \varepsilon_t \quad (5)$$

The last two columns of Table 3 present the findings of a two-stage least squares model using the instrumental variables, where the second-stage includes predicted *NETWORK_TOT* from the first-stage. We observe that the first-stage coefficients for *DIR_SUPPLY100* and *IND_NETWORK* are positive and significant, indicating that these two instrumental variables are a significant source of exogenous variation in *NETWORK_TOT* (meets the relevance condition). The Cragg-Donald Wald F and the Hausman (1978) endogeneity test provide further validation of the instrumental variables. The second-stage coefficient for *NETWORK_TOT* is positive and significant, supporting our baseline result that CEO network size increases the level of *RAM*.

A specific omitted variable issue is that CEO network size could relate to managerial ability so that more skillful CEOs conduct more *RAM*. To address this, we assign to each CEO observation a measure of managerial ability for the same firm-year. We use a proxy for managerial ability (Demerjian et al. 2012).[20] We then estimate Eq. (4), including *ABILITY* as an additional control variable. We continue to find a significantly positive coefficient for *NETWORK_TOT*, so that the main result in Table 3 holds after controlling for managerial ability.

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[19] Knyazeva et al. (2013) use the number of directors within 100 miles as an instrumental variable for board independence. They argue that proximity to larger pools of local director talent leads to more independent boards without directly influencing firm performance.

[20] Available at http://faculty.washington.edu/pdemerj/data.html.

Another concern is that the observations surrounding CEO transitions are particularly prone to simultaneity problems because both *RAM* and CEO network size can change for various reasons during this time. A CEO could be hired to improve accounting and reporting quality. In particular, "big bath" earnings adjustments could be made to make the new CEO look good. Henry and Schmitt (2001) show that firms are exposed to marginal downside risk by taking a big bath, yet a clear upside arises from recording the large and extreme losses this period, which reduce future periods of the burden and pave the way for a newly-appointed CEO to meet or beat an earnings benchmark in the future. Further, a board could consider network size in selecting a new CEO and appoint a better-networked candidate. These changes may lead to a spurious correlation between *RAM* and CEO network size. Therefore, as an additional test, we exclude the firm-year observations with a CEO change in the year of the change or one year later (*TENURE* = 0 or 1). Our findings in Table 3 remain similar after making this adjustment.

5.1.3 Other Robustness Tests

First, we consider alternative measures of CEO network size. Eq. (4) uses the number of direct connections to measure network size, which is a measure of the absolute degree centrality in graph theory. While it has been used in the literature for ease of interpretation (Engelberg et al. 2013; Javakhadze et al. 2016), other centrality measures may capture further aspects of connectedness. We consider four additional centrality measures as alternatives, reflecting: (i) how frequently the CEO lies on the shortest path between pairs of other individuals in the network (*betweenness*), (ii) the average degrees of separation between the CEO and others in the network (*closeness*), (iii) how well connected are those individuals who are in the CEO's network (*eigenvector*), and (iv) the number of first-degree connections in the network relative to total network degree (*relative degree*).[21] Online Supplement A indicates that our findings in Table 3 are robust to most of these alternatives. Second, we consider concerns that BoardEx individual educational backgrounds and other activities are self-reported and contain incomplete information. In an alternative specification, we use *Network_Employment* connections only since CEO employment histories are the most

[21] These measures are popular in the sociology literature and have been used in recent finance literature (Liu 2014; Hochberg et al. 2007; Renneboog and Zhao 2011). Appendix A of Liu (2014) states the mathematical definitions of the centrality measures used in this study.

accurate and complete. Our results are robust to this alternative network measure. Third, we use two alternative measures of *RAM*. Gunny (2010) suggests abnormal R&D expense and abnormal gain from asset sales as measures of *RAM*. We find our results hold using these two alternative R*AM* measures, that is, abnormal R&D expense and abnormal gain from asset sales also increase in CEO network size.

Fourth, we consider a possible spurious relation between network size and *RAM* that could arise if the level of *RAM* and executive network size follow a similar time trend. To control for this possibility, we estimate Eq. (4) as a time-series regression for each firm over the sample years 1999–2014. We then test whether the mean of the cross-sectional distribution of the *NETWORK_TOT* coefficients from the firm-level regressions is positive for *RAM*. We find that the mean coefficient under this time-series approach for *NETWORK_TOT* is significantly positive, which is the same result as in Table 3. The findings in Table 3 also hold for subsamples split on pre- and post-2002 Sarbanes-Oxley Act observations.

5.2 Influential or Informative Connections

If larger CEO networks increase *RAM* through information or power and influence channels, which is our main hypothesis, this also implies that the positive effect of network size on *RAM* should strengthen when the connections are more influential or informative. We consider three proxies, namely, CEO connections to executive versus non-executive directors (Section 5.2.1), CEO connections to people in large versus small firms (Section 5.2.2), and CEO connections to firms with higher use of RAM (Section 5.2.3). The findings summarized below indicate the cross-sectional patterns are consistent with this implication.

5.2.1 Connections to Executive vs. Non-Executive Directors

If the benefits of a large CEO network derive from shared information, then we should observe stronger results for networks whose information sharing relates to CEO connections with more influential people such as other CEOs or similar insider executives. There is a potential flipside, though, in that CEOs who benefit from greater information sharing from their networks could face steeper costs and risks to their reputation in the event of detected *RAM* linked to their CEO position. However, *RAM* has low detection risk compared to an equal adjustment from *AEM* or related practices (Cohen and Zarowin 2010). We use BoardEx's classification of *ED* (executive director) and *NED* (non-executive director) and contend that a CEO's link to a *NED* at another firm offers less ability to share information or enhance reputation than a link to an *ED* at another firm. Compared to non-executive directors, executive directors engage in firm business operations on a daily basis, thus having access to firm proprietary information. They also exert power and influence in the selection process of executive and non-executive members and mergers and acquisitions, thus influencing the labor market and takeover market. Prior studies show differences in findings consistent with this dichotomy (Adams and Ferreira 2007; Engelberg et al. 2012; Ravina and Sapienza 2010).

We test this idea by re-estimating Eq. (4) separately for *NETWORK_TOT* for *ED* and *NETWORK_TOT* for *NED* as the network size variables. Table 4 indicates the findings. Columns 1 and 2 of Table 4 confirm that the *NETWORK_TOT* coefficient for *ED* is more positive than for *NED*. Moreover, the difference between the coefficients (column 1), *ED-NED*, is significantly positive ($p<0.01$). These findings confirm that CEO networks with more information sharing and more ties to people of power and influence associate with higher levels of *RAM* (supports *H*2).

5.2.2 Connections to Large vs. Small Firms

Connections to people at large firms potentially provide access to more economically-significant information and may generate higher influence and expand outside employment options. If the underlying channel of network-induced *RAM* is driven by information or influence, we should expect a larger effect from the connections to large firms. To test this hypothesis, we measure network size for CEO connections involving S&P 500 firms versus others.[22] Columns 3 and 4 of Table 4 present the findings of re-estimating Eq. (4) with the number of connections to 500 firms (*S&P 500*) and the number of connections to non-S&P 500 firms (*Other*). The results show that the magnitude of the network effect on *RAM* is larger for connections to S&P 500 firms versus connections to other firms. The difference of the two coefficients is significant at the one percent level (column 3). These results indicate that the network benefits of *RAM* are higher for CEOs with network connections to large firms (supports *H2*).

22 Note that the CEO need not necessarily have a CEO position with an S&P 500 firm in year *t*. Rather, it is simply that the measurement of CEO network size captures ties to persons in other S&P 500 firms only.

5.2.3 *The Use of RAM by Connected Firms*

Assuming CEOs' decision-making process is influenced by the information percolating through their social connections, the use of *RAM* in connected firms will be especially relevant in affecting the level of *RAM* in the firm managed by the CEO. We, therefore, measure the average level of *RAM* over the prior three-years by the other firms in the CEO's network in the same 48 Fama-French industry category (*Connected_RAM*). Column 5 of Table 4 indicates that the coefficient for *Connected_RAM* is significantly positive ($p<0.05$). Thus, *RAM* not only associates with the overall size of the CEO's network, *NETWORK_TOT* but, also, with the use of *RAM* by other firms in the CEO network (*Connected_RAM*), which is direct evidence supporting the information channel of a social network. This is also consistent with the contagion effect of earnings management (Chiu et al. 2013), where extreme earnings management in one firm spreads to other firms through shared directors.

5.3 *Network-Induced RAM and Future Operating Performance*

5.3.1 *RAM and Future Operating Performance Conditional on Network Size*

While a large network reduces the net costs for the CEO to engage in a higher level of *RAM*, this behavior may not necessarily benefit the firm, as the prior literature on the relation between *RAM* and future operating performance shows mixed results (Gunny 2010; Leggett et al. 2009; Taylor and Xu 2010). This prior work does not, however, consider the role of CEO network size. CEOs with large networks could have higher private benefits and lower private costs from *RAM* because they are more capable of selecting a form of *RAM* with low detectability and are less concerned with poor long-run profitability due to labor market insurance. Therefore, we conjecture that the level of *RAM* chosen by well-connected CEOs would go beyond what is optimal for the firm. To test this hypothesis, we measure future operating performance as return on assets (*ROA*) or operating cash flow (*CFO*) in a future year relative to earnings management measurement in year *t*, where *ROA* equals net income before extraordinary items divided by the prior year's total assets.[23]

[23] We exclude $t+1$ to avoid the predictably negative relation between current accruals and next year's net income. Table 9 also excludes the results for $t+2$, as they are qualitatively the same as those for $t+3$.

Panel A of Table 5 reports the results of estimating the effects of *RAM* on future operating performance, split on small and large CEO network size. We regress *ROA* or *CFO* for year *t+3* on firm size (*SIZE*), book-to-market ratio (*BTM*), leverage (*LEV*), stock return (*RET*), insolvency risk (*ZSCORE*) for subsamples with CEOs with small and large networks (the results for *t*+1 and *t*+2 are similar). We expect that *RAM* conducted by well-connected CEOs will have a more negative effect on future firm performance. For the control variables, we expect significantly positive coefficients for all variables except *LEV*, which should relate negatively to future return performance, as high *LEV* suggests riskier operations.

Panel A of Table 5 indicates that higher *RAM* associates with lower future operating performance for large CEO networks. Moreover, the differences in the *RAM* coefficients for small and large networks in columns 1 and 2 are negative and significant for the two comparisons ($p<0.01$ for ROA_{t+3} and $p<0.05$ for CFO_{t+3}). We also show this in pooled regressions with an interaction term, that is, the coefficients in columns 3 and 6 for *RAM*NETWORK_TOT* are significantly negative ($p<0.01$). Hence, our findings indicate that although *RAM* per se may not be detrimental to the firm on average, the level of *RAM* induced by a large CEO network associates negatively with future operating return (*ROA*) or cash flow (*CFO*). These results, thus, support *H3*–that the relation between *RAM* and future firm performance is conditional on CEO network size.

Panel B of Table 5 refines *H3* by examining whether the negative association between *RAM* and future firm performance for large networks in Panel A is aggravated when the CEO holds a smaller ownership in the firm. The positive coefficients for *DIFF* in columns 1 and 3 of Panel B support this idea by showing that the relation between *RAM* and future operating performance is more negative when CEO ownership is low, consistent with the presence of agency costs from misaligned equity incentives.

These results also suggest that higher levels of *RAM* induced by large CEO networks could be more extreme than what is good for the firm or the CEO. For reputational reasons and through information shared in the network, a well-connected CEO may not be willing to engage in extreme or high levels of *RAM*, possibly because high or extreme *RAM* would be more detectable and generate lower future operating performance. To test this idea, we employ quantile regression method. The OLS estimates provide a statistically and economically significant and positive relationship between CEO network size and *RAM*.

However, the relationship can be nonlinear. Using the quantile regression method, we examine the relation between CEO network size and *RAM*, depending on the *RAM* distributions. Table 6 reports the findings. When levels of *RAM* is low, the coefficient for *NETWORK_TOT* is significantly positive with p-value < 0.01. But when levels of *RAM* is high, the coefficient for *NETWORK_TOT* is insignificant. Specifically, the relation between CEO network size and *RAM* is positive in the left tail where levels of *RAM* is low, but insignificant and negative in the right tail where levels of *RAM* is high. The difference in the magnitude of coefficients between 80 and 20 percentiles of *RAM* is significant. So, the CEO network size has asymmetric effects on firm real earnings management activities at the left and the right tails of *RAM* distribution. This result, thus, supports the view that the positive relation between network size and *RAM* (Tables 3 and 4) is more relevant when the level of *RAM* is lower or modest versus higher or extreme.

5.3.2 RAM to Beat an Earnings Benchmark

Gunny (2010) suggests that *RAM* in a particular setting may be beneficial to the firm by providing evidence that firms using *RAM* to beat an earnings benchmark have better future operating performance than those not using *RAM* to beat the benchmark (and, thus, using *RAM* for other reasons). We test whether the negative performance effect that we find is mitigated for well-connected CEOs engaging in this type of *RAM*. Following Gunny's approach, we identify firms that undertake *RAM* to just meet zero earnings or beat last year's earnings as those firm-years with net income or change in net income divided by total assets ≤ 0.01(*BENCH*). For different levels of adjusted *ROA* or adjusted *CFO* for *t*+1, we regress *NETWORK_TOT* on *RAM* with an interaction variable for *BENCH*RAM.* Table 7 shows mostly negative coefficients for the overall effect of *RAM* on future operating performance for well-connected CEOs (also shown in Table 5) but mostly positive coefficients for the interaction of *BENCH***RAM*. That is, *RAM* to beat the benchmark relates positively with future operating performance. We then split the sample on CEO network size. Columns 3 and 6 of Table 7 indicate that the coefficient for *BENCH*RAM* is significantly positive for firms with large CEO networks (*Top Tercile*) but not for firms with small CEO networks (*Bottom Tercile*). The latter have small or negative interaction coefficients (columns 2 and 4). Thus, we extend Gunny (2010) by showing that the positive coefficient for *BENCH***RAM* concentrates in the sample where CEO network size is large. In other words, the overall negative effect of *RAM* on future operating performance (Table 5) is attenuated if well-connected CEOs undertake *RAM* to meet an earnings benchmark (Table 7).

5.3.3 Reining in Network-Induced RAM with CEO Share Ownership

Given our finding in Table 5 that higher *RAM* associates with lower future operating performance for firms with large CEO networks, the potential gains from this earnings management practice accrue to the CEO rather than the firm. As such, higher levels of *RAM* related to large CEO networks may be considered as an agency problem. If CEO and shareholder interests do not align well (e.g., the CEO has low ownership), the CEO might act more opportunistically. Because the cost of *RAM* to the CEO is low even though the cost to firm value could be high, we should observe a stronger positive relation between *NETWORK_TOT* and *RAM* when a well-connected CEO has *low* share ownership. We find this result in Table 8. The coefficient for *NETWORK_TOT*Ownership* is significantly negative (column 1), and the positive coefficient for *NETWORK_TOT* for lower CEO ownership (column 2) is significantly greater than the *NETWORK_TOT* coefficient for higher ownership (column 3), which is significantly negative.[24]

5.4 CEO Network Size and Other Types of Earnings Management

We argue that the low detectability and cash flow consequences of *RAM* can make it more preferable for CEOs with large networks due to lower net private costs. We broaden our inquiry by examining whether the effect of CEO network size varies for other proxies for earnings management that CEOs might consider as alternatives. As detailed below, network size varies negatively with restatements (Table 9) and a proxy for *AEM* (Table 10). These tests distinguish *RAM* from other means to manage earnings, where a large network could have the opposite effects on the earnings management practice.

5.4.1 Restatements

We consider a restatement as evidence of a material accounting irregularity (that more-likely-than-not reflects *AEM*) in an earlier period. Restatements also associate with poorer future job prospects for terminated CEOs (Desai et al. 2006). To estimate the relation between restatements and network size, we re-estimate Eq. (4) as a logistic regression by replacing the dependent variable *RAM* with *Restatement*, set

[24] The negative relation between *RAM* and future operating performance for well-connected CEOs (Panel A of Table 7) is also more negative for CEOs with lower ownership in the firm (Panel B of Table 7).

equal to one for firm-years with a restatement announcement relating to the Audit Analytics categories of financial fraud, errors, and regulatory investigation (www.auditanalytics.com) and zero otherwise. Because *AEM* has been linked a future restatement (Ettredge et al. 2010; Richardson et al. 2002), we lag *AEM* as a control variable by one year in Eq. (4). We expect CEOs with larger networks to refrain from this detected form of irregularity, as a restatement represents a material correction to a firm's earnings and shareholders' equity. The findings in Table 9 confirm this expectation and show significantly negative coefficients ($p<0.05$) for *NETWORK_TOT* for both specifications of Eq. (4) estimated as a logistic regression with *Restatement* as the dependent variable. Thus, *Restatement*, which represents the outcome of an accounting irregularity (e.g., a GAAP violation) in a prior period, associates negatively with CEO network size.

5.4.2 Accrual Earnings Management

While *AEM* may not always be opportunistic or intentional, a large discretionary accrual could constitute a departure from GAAP, potentially reportable by the auditor.[25] This could result in additional outside scrutiny, a restatement, an Securities and Exchange Commission (SEC) investigation, or class action or enforcement litigation (Dechow et al. 2012; Dechow et al. 1995; Dechow et al. 1996; DuCharme et al. 2004; Gong et al. 2008; Karpoff et al. 2008a; Richardson et al. 2002; Zang 2012). Also, survey results show that CEOs perceive *AEM* as more ethically questionable than other forms of earnings management (Coram et al. 2016). Given this evidence, we predict that well-connected CEOs with more social capital to lose will reflect lower levels of *AEM*. Supporting this argument, Table 10 indicates that when *AEM* is regressed onto *NETWORK_TOT* and controls, the coefficient for *NETWORK_TOT* is negative or insignificant ($p<0.01$). This result implies that greater CEO network size amplifies the regulatory and reputational costs of *AEM*, limiting the size of the *AEM* adjustment. It is also consistent with Bhandari et al. (2018), who report a negative relation between the level of *AEM* and CEO network size.

Further, we predict that the effect of CEO network size on *AEM* should be stronger at the right tail of the *AEM* distribution, suggesting that a higher level of *AEM* generates an expectation of higher legal and

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[25] Jeffrey Immelt, the successor chairman at GE, with fewer social connections than its former legendary CEO, Jack Welch (according to our data set), was reported to have engaged in *AEM*. As a result, he incurred substantial reputational and regulatory costs, including a $50 million fine paid to the SEC.

reputational costs. By contrast, the use of a lower level of *AEM* could be warranted on the basis of judgment within accounting choice under the Supreme Court ruling in the Tellabs decision (Tellabs, Inc. v. Makor Issues & Rights, Ltd., No. 06-484, 437 F. 3d 588), which allows for reasonable, i.e., more-likely-than-not, explanations of accounting choice as a defense against plaintiffs' allegations. The cost and litigation risk associated with a lower level of *AEM* could, therefore, be lower than for a higher level of *AEM*. Supporting this argument, columns 3 and 4 of Table 10 show that when we split our sample on *Large AEM* and *Small AEM* and run the regression of *AEM* onto *NETWORK_TOT* and controls, the coefficient of *NETWORK_TOT* is more negative and significant for the *Large AEM* subgroup ($p<0.05$).

6. Conclusion

Based on established proxies for real activities management (*RAM*), and after employing a wide array of controls for other possible factors, we find a positive relation between CEO network size and the level of *RAM*. We theorize that this positive relation occurs because the information-sharing and power and influence channels from a large CEO social network enable the use of *RAM* to confer net benefits on a connected executive. This may even make the practice firm-wise desirable in the short term because the firm reports a superior trend of earnings, beats earnings benchmarks, and may reduce information asymmetry, all of which can increase firm value. In the long term, however, we show that large *RAM* adjustments by well-connected CEOs associate with worse future firm performance, even in the absence of detection. But with labor and takeover market insurance, a well-connected CEO may not care about the possibility of worse future firm performance from the consequences of departures from normal or optimal operations from *RAM*. These CEO network benefits may also explain the pervasive and popular use of *RAM* in practice. To our knowledge, we are the first to show that larger CEO networks associate with higher levels of *RAM*. Those higher earnings adjustments, however, can degrade firm performance in the longer term. Thus, when a large CEO network amplifies the power and influence of the top executive, our study indicates that such CEO networks have a darker side regarding future firm performance.

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Appendix A. Variable Definitions

Earnings Management and Network Variables:		
AEM	=	Accrual based earnings management measure, firm's current discretionary accrual.
CF_RAM	=	Abnormal cash flow from operations, measured as the deviations from the predicted values of the corresponding industry-year regression and then multiply -1. High value represents more abnormal level of operating cash flow.
DISEXP_RAM	=	Abnormal discretionary expenses, measured as the deviations from the predicted values of the corresponding industry-year regression and then multiply -1. High value represents more abnormal level of discretionary expenses.
Network_Education	=	Summation (in thousand) of the CEO’s educational ties. An educational tie occurs if the CEO went to the same university at the same time with another executive or director.
Network_Employment	=	Summation (in thousand) of the CEO's employment ties. An employment tie occurs if the CEO currently or historically overlapped with another executive or director
Network_OtherActivity	=	Summation (in thousand) of the CEO’s other activity ties. Another activity tie occurs if the CEO participated in a same organization (e.g., charity or recreational club) at the same time as another executive or director.
NETWORK_TOT	=	Summation (in thousands) of *Network_Employment*, *Network_Education*, and *Network_OtherActivity*.
Connected_RAM	=	The average *RAM* in the prior three years of other firms in the same Fama-French industry category.
PROD_RAM	=	Abnormal production cost, measured as the deviations from the predicted values of the corresponding industry-year regression and then multiply -1. High value represents more abnormal level of production cost.
RAM	=	Total amount of real transactions management, computed as the sum of *CFRAM*, *PRODRAM* and *DISEXPRAM*, as defined by Cohen et al. (2008).
Other Variables:		
Analyst_Error	=	Analyst forecast error that is measured as the difference between actual earnings per share.
BIG4	=	1 if the firm is audited by a Big 4 CPA firm, and 0 otherwise.
BTM	=	Book to market ratio.
CEO_AGE	=	Natural log of one plus CEO’s age at the fiscal year t.
CEO_DUAL	=	1 if the CEO has the dual positions of chairman at the beginning of the fiscal year containing quarter t-1, and 0 otherwise
CEO_TENURE	=	Number of years that the CEO has held the position of chief executive officer as of the beginning of the fiscal year
CFVOL	=	Standard deviation of operating cash flow on asset for five years.
CYCLE	=	Thousand days receivable plus the days inventory less the days payable.
DIR_SUPPLY100	=	Number of directors in the same industry (based on 2-digit SIC code) within 100 miles of the firm’s headquarters.
EVOL	=	Standard deviation of ROA for five years.
IND_NETWORK	=	Average network size for the *other* firms in the dataset in the same industry (based on the Fama-French 48 industry classification).
INDADJ_ROE	=	Firm’s return on equity minus industry ROE. Industry ROE is calculated as the mean ROE of firms in the same industry (based on 2-digit SIC code) for the same period.
INSTOWN	=	Percentage of outstanding shares owned by institutions.
LEV	=	Firm’s leverage ratio, measured as long-term liabilities divided by total assets.
LNSALE	=	Natural log of sales at year t.
MKT_SHARE	=	Herfindahl index using two-digit SIC-codes
NOA	=	1 if the net operating assets (i.e., shareholders’ equity less cash and marketable securities and plus total debt) at the beginning of the year divided by lagged sales is above the median of the corresponding industry-year, and 0 otherwise.
Ownership	=	Percentage of common shares in firm held by the CEO at year t.
Post_Position	=	1 if the departed CEO has a new full-time position in another organization within two years of turnover, and 0 otherwise.
RET	=	Firm's raw return for the fiscal year t.
RETVOL	=	Standard deviation of monthly raw stock returns for five years.
ROA	=	Income before extraordinary items divided by total assets.
SALES_GROWTH	=	One-year sales growth ratio.
SIZE	=	Natural log of market value.
ZSCORE	=	Altman’s Z-score (Altman 1968, 2000)

Table 1. Sample Distribution

Panel A. Sample distribution by fiscal year

Fiscal Year	Frequency	Percent
1999	66	0.27
2000	651	2.65
2001	813	3.31
2002	861	3.51
2003	1,717	6.99
2004	1,914	7.80
2005	1,966	8.01
2006	1,913	7.79
2007	1,805	7.35
2008	1,806	7.36
2009	1,703	6.94
2010	1,696	6.91
2011	1,966	8.01
2012	1,962	7.99
2013	1,986	8.09
2014	1,724	7.02
Total	24,549	100.00

Panel B. Sample distribution by Fama-French 48 industry classification

Industry	Frequency	Percent	Industry	Frequency	Percent
Agriculture	61	0.25	Machinery	1,066	4.34
Aircraft	156	0.64	Measuring Equipment	744	3.03
Apparel	390	1.59	Medical Equipment	1,201	4.89
Automobiles and Trucks	431	1.76	Industrial Metal Min..	267	1.09
Beer & Liquor	109	0.44	Other Industries	117	0.48
Business Services	3,812	15.53	Personal Services	240	0.98
Business Supplies	320	1.30	Petroleum and Natural Gas	1,817	7.40
Candy & Soda	98	0.40	Pharmaceutical Products	1,486	6.05
Chemicals	736	3.00	Precious Metals	254	1.03
Coal	111	0.45	Printing and Publishing	214	0.87
Computers	1,171	4.77	Recreation	230	0.94
Construction	240	0.98	Restaurants, Hotels, Motels	460	1.87
Construction Materials	661	2.69	Retail	1,689	6.88
Consumer Goods	484	1.97	Rubber and Plastic Products	195	0.79
Defense	86	0.35	Railroad Equipment	52	0.21
Electrical Equipment	573	2.33	Shipping Containers	84	0.34
Electronic Equipment	2,378	9.69	Steel Works Etc	418	1.70
Entertainment	385	1.57	Textiles	84	0.34
Fabricated Products	59	0.24	Trading	236	0.96
Food Products	518	2.11	Transportation	59	0.24
Healthcare	484	1.97	Wholesale	373	1.52
			Total	24,549	100.00

Table 2. Descriptive Statistics

Variable	N	Mean	Std. dev.	25%-tile	Median	75%-tile
NETWORK_TOT	24,549	0.145	0.197	0.011	0.061	0.198
NETWORK_TOT based on executive director networks *(ED)*	24,549	0.025	0.034	0.003	0.011	0.033
NETWORK_TOT based on non-executives director networks *(NED)*	24,549	0.155	0.180	0.031	0.083	0.210
S&P 500	24,549	0.058	0.086	0.003	0.022	0.075
OTHER	24,549	0.122	0.135	0.028	0.071	0.164
RAM	24,549	-0.025	0.987	-0.250	0.027	0.294
AEM	24,549	0.001	0.058	-0.023	0.001	0.027
SIZE	24,549	6.192	2.062	4.815	6.243	7.548
BTM	24,549	0.532	0.516	0.244	0.435	0.716
ROA	24,549	-0.083	2.896	-0.034	0.036	0.080
LEV	24,549	0.172	0.363	0.000	0.103	0.263
EVOL	24,549	0.093	0.166	0.016	0.037	0.095
CFVOL	24,549	0.067	0.086	0.021	0.041	0.076
CYCLE	24,549	0.060	0.140	0.023	0.064	0.115
SALES_GROWTH	24,549	0.004	0.140	0.000	0.001	0.002
MKT_SHARE	24,549	0.064	0.053	0.033	0.043	0.078
ZSCORE	24,549	0.573	4.494	0.463	1.601	2.490
NOA	24,549	0.679	0.467	0.000	1.000	1.000
INSTOWN	24,549	0.549	0.413	0.083	0.610	0.906
CEO_AGE	24,549	4.019	0.145	3.932	4.025	4.127
CEO_TENURE	24,549	1.518	0.809	0.875	1.504	2.092
BIG4	24,549	0.745	0.436	0.000	1.000	1.000

This table summarizes the sample descriptive statistics. The sample comprises 24,549 firm-years with BoardEx and other data over 1999–2015, representing 4,226 different firms. Appendix A defines the variables.

Table 3. CEO Network Size and *RAM*: OLS and Two-Stage Least Squares

		OLS	*Two-stage Least Squares*	
Dependent Variable =	*RAM*	*RAM*	*1st Stage NETWORK_TOT*	*2nd Stage = RAM*
	(1)	(2)	(3)	(4)
NETWORK_TOT	0.0465	0.0388		0.6458
	(2.95)***	(3.27)***		(2.38)**
Controls:				
AEM	0.3096	0.2947	-0.0455	0.9120
	(3.58)***	(3.23)***	(-2.45)**	(2.53)**
SIZE	-0.0201	-0.0197	0.0440	-0.0588
	(-2.40)**	(-2.42)**	(57.56)***	(-4.19)***
BTM	0.1746	0.1715	0.0267	0.0965
	(4.14)***	(4.16)***	(10.73)***	(4.06)***
ROA	0.0021	0.0020	-0.0339	-0.7308
	(0.57)	(0.55)	(-4.85)***	(-6.27)***
LEV	0.1654	0.1638	0.0469	0.3389
	(4.40)***	(4.41)***	(7.48)***	(5.43)***
EVOL	-0.1067	-0.0978	0.0116	-0.4453
	(-0.89)	(-0.78)	(1.23)	(-2.22)**
CFVOL	-1.1053	-1.0961	-0.0971	-0.7463
	(-5.01)***	(-5.08)***	(-5.57)***	(-2.49)**
CYCLE	0.2471	0.2368	-0.0003	0.0066
	(2.04)**	(1.96)*	(-1.09)	(0.82)
SALES_GROWTH	-0.1128	-0.1130	-0.0116	-0.0823
	(-1.58)	(-1.62)	(-1.17)	(-0.84)
MKT_SHARE	-0.1286	-0.1221	-0.0167	0.0075
	(-0.96)	(-0.89)	(-0.53)	(0.03)
ZSCORE	-0.0126	-0.0127	-0.0021	0.0185
	(-3.66)***	(-3.66)***	(-5.63)***	(2.65)***
NOA	0.1147	0.1154	-0.0295	0.2127
	(5.23)***	(5.36)***	(-10.11)***	(6.03)***
INSTOWN	-0.0498	-0.0482	-0.0131	-0.1002
	(-2.86)***	(-2.82)***	(-4.29)***	(-3.18)***
CEO_AGE		0.2904	0.0303	0.4679
		(2.30)**	(3.88)***	(4.54)***
CEO_TENURE		-0.0160	-0.0113	-0.0143
		(-1.69)*	(-8.11)***	(-0.81)
Instrumental variables:				
DIR_SUPPLY100			0.0228	
			(2.14)**	
IND_NETWORK			0.8549	
			(18.91)***	
Partial F-Statistic			88.89	(<0.0001)
Under-identification test (Chi square)			151.45	(<0.0001)
Weak Identification Test (Cragg Donald Wald F)			75.47	(<0.0001)
Endogeneity Test (Chi square)			5.97	(<0.05)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	24,549	24,549	23,211	23,211
Adjusted R^2	0.0621	0.0636	0.219	0.0150

This table reports the results of examining the effect of CEO network size on *RAM*. Columns 1 and 2 report the results of an OLS regression examining the effect of CEO network size on *RAM*. These columns present the OLS regression coefficients and two-sided *t*-values for the maximum samples of 24,549 firm-years. Columns 3 and 4 present the results of a two-stage regression using the executive/directors within 100 miles geographically and the industry average CEO total network size as the instrumental variables. In the first-stage regression the dependent variable is the CEO's network size. In the second-stage regression *RAM* is the dependent variable and the predicted value of CEO network size is the test variable. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 4. CEO Network Size and *RAM*: Network Characteristics

Variables	*RAM*	*RAM*	*RAM*	*RAM*	*RAM*
	(1)	(2)	(3)	(4)	(5)
NETWORK_TOT for executive directors (*ED*)	0.1794 (11.72)***				
NETWORK_TOT for non-executive (*NED*)		0.0577 (3.33)***			
S&P 500			0.1902 (6.63)***		
Other				0.0455 (1.51)	
NETWORK_TOT					0.0622 (2.34)**
CONNECTED_RAM					0.2790 (2.66)***
Difference (*ED* – *NED*)	0.1217 (5.47)***				
Difference (*S&P 500* – *Other*)			0.1447 (3.74)***		
Firm Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	24,549	24,549	24,549	24,549	18,847
Adjusted R^2	0.0636	0.0637	0.0637	0.0636	0.0199

This table reports the results of OLS regressions examining the effect of CEO network characteristics on *RAM* for samples of 24,549 firm-years. The first two columns (1 and 2) are based on networks with executive (ED) versus non-executive (NED) directors. The next two columns (3 and 4) are based on the size of the firm (*S&P 500* versus *Other)*. The last column (5) controls for the prior three-year average level of *RAM* by the other firms in the CEO's network in the same 48 Fama-French industry category. We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 5. *RAM* and Future Operating Performance

Panel A: Conditional on CEO Network Size

Network size	*Small*	*Large*	*Full Sample*	*Small*	*Large*	*Full Sample*
Dependent Variable =	*ROA t+3*	*ROA t+3*	*ROA t+3*	*CFO t+3*	*CFO t+3*	*CFO t+3*
	(1)	(2)	(3)	(4)	(5)	(6)
RAM	0.0035	-0.0039	0.0016	0.0010	-0.0038	0.0010
	(2.18)**	(-2.68)**	(1.06)	(1.04)	(-2.27)**	(1.06)
DIFF (Large – Small)	-0.0074			-0.0048		
	(-3.44)***			(-2.59)**		
SIZE	0.0432	0.0342	0.0395	0.0285	0.0263	0.0279
	(13.71)***	(16.23)***	(16.13)***	(20.29)***	(19.36)***	(21.95)***
BTM	0.0111	0.0000	0.0000	0.0037	0.0000	0.0000
	(3.16)***	(6.03)***	(6.96)***	(4.18)***	(6.37)***	(6.92)***
LEV	-0.0321	-0.0679	-0.0589	0.0027	-0.0325	-0.0175
	(-1.59)	(-3.42)***	(-4.95)***	(0.26)	(-3.05)***	(-4.46)***
RET	0.0031	0.0028	0.0029	0.0014	0.0020	0.0016
	(7.77)***	(6.56)***	(7.49)***	(6.12)***	(10.30)***	(8.38)***
ZSCORE	0.0000	0.0013	0.0000	0.0000	0.0004	0.0000
	(4.07)***	(1.84)*	(3.91)***	(7.45)***	(1.01)	(5.59)***
NETWORK_TOT			-0.0371			-0.0397
			(-5.76)***			(-9.58)***
RAM NETWORK_TOT*			-0.0450			-0.0715
			(-3.05)***			(-6.61)***
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,820	8,664	17,484	8,765	8,625	17,390
Adj. R^2	0.141	0.215	0.163	0.168	0.229	0.195

Continued on next page.

Table 5, contd. *RAM* and Future Operating Performance

Panel B: Conditional on CEO Ownership

CEO Ownership	*Higher Ownership*	*Lower Ownership*	*Higher Ownership*	*Lower Ownership*
Dependent Variable =	*ROA t+3*	*ROA t+3*	*CFO t+3*	*CFO t+3*
	(1)	(2)	(3)	(4)
RAM	0.0021	-0.0009	-0.0011	-0.0019
	(2.05)**	(-0.31)	(-0.59)	(-0.89)
SIZE	0.0315	0.0370	0.0247	0.0271
	(10.12)***	(11.65)***	(13.36)***	(15.02)***
BTM	-0.0046	0.0007	-0.0015	0.0001
	(-2.28)**	(1.44)	(-1.06)	(0.33)
LEV	0.0088	-0.0954	0.0191	-0.0426
	(0.53)	(-3.30)***	(1.64)	(-2.27)**
RET	0.0014	0.0028	0.0009	0.0014
	(3.06)***	(5.30)***	(2.36)**	(5.83)***
ZSCORE	0.0056	0.0014	0.0048	0.0005
	(1.67)*	(2.06)**	(2.50)**	(1.10)
NETWORK_TOT	-0.0414	-0.0086	-0.0456	-0.0217
	(-5.22)***	(-0.67)	(-8.99)***	(-2.90)***
RAM NETWORK_TOT*	-0.0164	0.0014	-0.0083	0.0043
	(-8.51)***	(0.22)	(-2.77)***	(1.50)
DIFF (Higher – Lower)	0.0178		0.0126	
	(4.48)***		(3.30)***	
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	8,820	8,664	8,765	8,625
Adj. R^2	0.141	0.215	0.168	0.229

This table reports the results of OLS regressions examining the effect of *RAM* on future operating performance, split on network size (Panel A) and CEO ownership (Panel B). We report t-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 6. Quantile Regression Analysis of *RAM* and CEO Network Size

	RAM	
INDEP	*NETWORK_TOT*	
	Coeff.	t-stat
OLS	0.0388	(3.27)***
Quantile		
0.10	0.0875	(3.50)***
0.20	0.0567	(3.49)***
0.30	0.0347	(2.59)***
0.40	0.0171	(1.34)
0.50	0.0073	(0.61)
0.60	-0.0020	(-0.17)
0.70	-0.0136	(-1.06)
0.80	0.0119	(0.79)
0.90	0.0114	(0.52)
Observations		24,549
Avg Pseudo R2		0.0866
Q(0.90)=Q(0.10)	-0.07610	-2.47**
Q(0.80)=Q(0.20)	-0.04480	-2.14**
Q(0.90)=Q(0.50)	0.00410	0.19
Q(0.10)=Q(0.50)	0.08020	3.09***

This table reports the result for a quantile regression analysis, examining the effect of CEO network size on *RAM* conditional on the size of *RAM*. This table presents the OLS regression coefficients for samples of 24,549 firm-years. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 7. *RAM*, Earnings Benchmarks, and Future Operating Performance Conditional on Network Size

Dependent variable =	CEO Network Size			CEO Network Size		
Sample	*Full Sample CFO t+1*	*Bottom Tercile CFO t+1*	*Top Tercile CFO t+1*	*Full Sample ROA t+1*	*Bottom Tercile ROA t+1*	*Top Tercile ROA t+1*
	(1)	(2)	(3)	(4)	(5)	(6)
BEAT	0.0008	0.0029	-0.0040	0.0115	0.0162	0.0082
	(0.24)	(0.62)	(-0.93)	(1.53)	(1.50)	(0.89)
JUSTMISS	-0.0040	0.0028	-0.0137	-0.0097	-0.0150	-0.0082
	(-0.75)	(0.46)	(-1.99)**	(-1.26)	(-2.09)**	(-1.09)
BENCH	0.0003	0.0156	-0.0164	0.0004	0.0042	-0.0005
	(0.05)	(1.66)*	(-5.04)***	(0.05)	(0.34)	(-0.10)
RAM	-0.0118	-0.0089	-0.0143	0.0006	0.0008	-0.0039
	(-6.06)***	(-1.93)*	(-5.01)***	(0.17)	(0.12)	(-1.35)
*BENCH*RAM*	0.0006	-0.0142	0.0203	0.0124	0.0008	0.0181
	(0.09)	(-1.08)	(1.76)*	(1.69)*	(0.05)	(1.70)*
DIFF (Top-Bottom)		0.0345			0.0173	
		(1.98)**			(0.90)	
ROA	0.3039	0.2927	0.3010	0.4429	0.4250	0.4115
	(7.44)***	(6.02)***	(5.97)***	(8.44)***	(5.25)***	(6.80)***
SIZE	0.0074	0.0070	0.0072	0.0057	0.0023	0.0079
	(5.66)***	(5.61)***	(4.42)***	(6.65)***	(1.95)*	(5.92)***
BTM	-0.0132	-0.0109	-0.0198	-0.0291	-0.0302	-0.0296
	(-3.13)***	(-2.39)**	(-3.75)***	(-4.63)***	(-4.50)***	(-2.71)***
RET	-0.0010	0.0024	-0.0042	0.0077	0.0108	0.0074
	(-0.97)	(1.23)	(-1.31)	(3.62)***	(2.97)***	(1.84)*
ZSCORE	0.0126	0.0155	0.0120	0.0151	0.0210	0.0133
	(5.13)***	(5.17)***	(4.05)***	(4.54)***	(5.88)***	(3.88)***
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,377	5,821	5,775	17,377	5,821	5,775
Adjusted R^2	0.460	0.466	0.457	0.448	0.465	0.418

This table extends the model in Gunny (2010) by showing that the relation between *RAM* and CFO_{t+1} (columns 1–3) and ROA_{t+1} (columns 4–6) when *RAM* is used to meet a benchmark varies conditional on CEO Network Size. The incremental effect of *RAM* on *CFO*/*ROA* to meet a benchmark is shown as the coefficient for *BENCH*RAM*. The difference in the coefficient for *BENCH*RAM* for large and small networks is the effect on *BENCH*RAM* of CEO Network Size. We report t-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 8. CEO Network Size and *RAM* Conditional on CEO Share Ownership

CEO Share Ownership	*Full Sample*	*Lower Ownership*	*Higher Ownership*
Dependent Variable	RAM	*RAM*	*RAM*
	(1)	(2)	(3)
NETWORK_TOT	0.1202	0.0805	-0.1042
	(3.79)***	(2.14)**	(-2.17)**
Ownership	-0.1549		
	(-1.11)		
*NETWORK_TOT*Ownership*	-2.8622		
	(-3.05)***		
DIFF (Lower - Higher)		-0.1847	
		(-3.23)***	
AEM	0.2635	0.6352	0.3092
	(3.44)***	(2.57)**	(2.05)**
SIZE	-0.0170	0.0085	-0.0463
	(-2.22)**	(4.53)***	(-3.09)***
BTM	0.2149	0.2645	0.1698
	(4.26)***	(6.06)***	(2.96)***
ROA	-0.0780	-0.2539	-0.0767
	(-1.51)	(-1.86)*	(-1.29)
LEV	0.2379	0.0424	0.3903
	(2.96)***	(0.61)	(2.66)***
EVOL	-0.1611	-0.3332	-0.1181
	(-1.26)	(-1.21)	(-1.27)
CFVOL	-1.2342	-1.0460	-1.2847
	(-3.78)***	(-2.27)**	(-4.57)***
CYCLE	0.2726	0.2245	0.3179
	(1.94)*	(1.27)	(2.51)**
SALES_GROWTH	-0.2757	-1.7926	-0.3464
	(-1.32)	(-0.67)	(-1.38)
MKT_SHARE	-0.0944	-0.7129	0.5458
	(-0.38)	(-2.45)**	(1.55)
ZSCORE	-0.0109	-0.0118	-0.0064
	(-4.96)***	(-1.92)*	(-0.81)
NOA	0.1137	0.0128	0.1790
	(8.68)***	(1.04)	(5.07)***
INSTOWN	-0.1058	-0.0715	-0.0745
	(-2.56)**	(-2.52)**	(-1.61)
CEO_AGE	0.3002	0.3626	0.2045
	(2.24)**	(2.04)**	(1.50)
CEO_TENURE	-0.0002	-0.0203	0.0134
	(-0.01)	(-0.94)	(0.64)
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	11,637	5,812	5,825
Adjusted R^2	0.0753	0.0893	0.0678

This table reports the results of OLS regressions examining the effect of CEO network size on *RAM* conditional on the degree of CEO ownership in the firm. We report *t*-statistics in parentheses with standard errors clustered by firm. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 9. CEO Network Size and Restatements

Dependent variable =	*Restatement*	*Restatement*
NETWORK_TOT	-0.4248	-0.4279
	(-2.30)**	(-2.26)**
AEM $_{t-1}$	-0.4066	-0.4430
	(-0.69)	(-0.74)
AEM $_{t-2}$	0.6487	0.5802
	(1.28)	(1.16)
SIZE	-0.0516	-0.0506
	(-1.63)	(-1.65)*
BTM	0.0146	-0.0066
	(0.11)	(-0.05)
ROA	0.0205	0.0234
	(0.09)	(0.11)
LEV	0.3377	0.3352
	(1.99)**	(2.01)**
EVOL	0.0217	0.0961
	(0.04)	(0.18)
CFVOL	-0.3459	-0.2969
	(-0.58)	(-0.48)
CYCLE	-0.0133	-0.0134
	(-4.55)***	(-4.35)***
SALESGROWTH	-9.7095	-9.0889
	(-1.47)	(-1.42)
HHI	-0.4463	-0.3885
	(-0.79)	(-0.71)
ZSCORE	-0.0105	-0.0134
	(-0.75)	(-0.98)
NOA	-0.0448	-0.0393
	(-0.50)	(-0.46)
INSTOWN	0.1863	0.2041
	(1.58)	(1.70)*
BIG4	0.0742	0.0922
	(0.82)	(1.00)
LNAGE		0.7620
		(3.33)***
LNTENTURE		0.0109
		(0.27)
Industry Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	10,380	10,380
Pseudo R^2	0.039	0.0405

This table reports the results of examining the effect of CEO network size on *Restatement*. It reports the results of an OLS regression examining the effect of CEO network size on *RAM*. These columns present the logistic regression coefficients and two-sided *t*-values for the maximum samples of 10,380 firm-years. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

Table 10. CEO Network Size and *AEM*

			Level of Earnings Management	
Dependent Variable =	*AEM*	*AEM*	*Small AEM*	*Large AEM*
	(1)	(2)	(3)	(4)
NETWORK_TOT	-0.0053	-0.0055	-0.0017	-0.0103
	(-3.07)***	(-3.08)***	(-2.00)**	(-2.70)***
DIFF (Large – Small)			-0.0086	
			(-2.36)**	
RAM	0.0011	0.0010	-0.0002	0.0021
	(2.05)**	(1.98)**	(-4.17)***	(2.51)**
SIZE	-0.0001	-0.0001	0.0002	-0.0002
	(-0.26)	(-0.26)	(1.46)	(-0.22)
BTM	-0.0017	-0.0018	0.0000	-0.0041
	(-0.89)	(-0.92)	(0.07)	(-1.21)
ROA	0.0004	0.0004	0.0004	0.0003
	(2.39)**	(2.38)**	(0.68)	(1.88)*
LEV	0.0044	0.0043	0.0000	0.0052
	(2.39)**	(2.35)**	(0.08)	(2.29)**
EVOL	0.0003	0.0006	-0.0018	0.0036
	(0.05)	(0.12)	(-2.31)**	(0.41)
CFVOL	0.0042	0.0046	0.0042	0.0047
	(0.53)	(0.58)	(1.64)	(0.40)
CYCLE	0.0125	0.0122	0.0012	0.0195
	(2.45)**	(2.38)**	(0.89)	(1.96)*
SALES_GROWTH	0.0054	0.0054	0.0003	0.0087
	(1.39)	(1.37)	(1.78)*	(1.94)*
MKT_SHARE	0.0122	0.0123	-0.0026	0.0263
	(0.79)	(0.80)	(-0.69)	(0.94)
ZSCORE	0.0006	0.0006	-0.0001	0.0010
	(2.55)**	(2.56)**	(-1.54)	(2.77)***
NOA	0.0042	0.0042	0.0003	0.0079
	(2.51)**	(2.51)**	(0.59)	(2.64)***
	-0.0027	-0.0027	-0.0005	-0.0041
	(-1.83)*	(-1.81)*	(-1.32)	(-1.48)
BIG4	-0.0005	-0.0002	-0.0003	0.0003
	(-0.49)	(-0.19)	(-1.09)	(0.13)
CEO_AGE		0.0090	0.0017	0.0167
		(1.82)*	(2.32)**	(1.83)*
CEO_TENURE		-0.0002	0.0001	-0.0003
		(-0.31)	(0.73)	(-0.26)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	24,549	24,549	12,284	12,265
Adjusted R^2	0.0234	0.0237	0.0131	0.0376

This table reports the results of examining the effect of CEO network size on *AEM*. Columns 1 and 2 report the results of an OLS regression examining the effect of CEO network size on *RAM*. These columns present the OLS regression coefficients and two-sided *t*-values for the maximum samples of 24,549 firm-years. Columns 3 and 4 present the results of examining the effect of CEO network size on *AEM,* after splitting our sample into *Large* and *Small* subgroups of *AEM*, based on the sample median of *AEM*. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Appendix A defines the variables.

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Table A CEO Network Size and *RAM*: Alternative Measures of Network Size

Dependent variable =	*Betweenness*	*Closeness*	*Eigenvector*	*rDegree*
Betweenness	0.1270			
	(3.20)***			
Closeness		0.4022		
		(2.04)**		
Eigenvector			-0.0173	
			(-0.20)	
rDegree				6.7115
				(2.73)***
AEM	0.2936	0.2936	0.2924	0.2957
	(3.24)***	(3.20)***	(3.24)***	(3.24)***
SIZE	-0.0195	-0.0208	-0.0178	-0.0200
	(-2.33)**	(-2.51)**	(-2.18)**	(-2.60)***
BTM	0.1713	0.1709	0.1727	0.1711
	(4.13)***	(4.15)***	(4.17)***	(4.17)***
ROA	0.0020	0.0020	0.0020	0.0021
	(0.55)	(0.54)	(0.54)	(0.55)
LEV	0.1642	0.1631	0.1645	0.1639
	(4.38)***	(4.35)***	(4.38)***	(4.37)***
EVOL	-0.0982	-0.1007	-0.0969	-0.0987
	(-0.79)	(-0.80)	(-0.78)	(-0.79)
CFVOL	-1.0953	-1.0886	-1.1006	-1.0941
	(-5.03)***	(-5.03)***	(-5.05)***	(-5.07)***
CYCLE	0.2374	0.2351	0.2364	0.2376
	(1.96)*	(1.96)*	(1.95)*	(1.97)**
SALES_GROWTH	-0.1128	-0.1121	-0.1129	-0.1128
	(-1.62)	(-1.60)	(-1.62)	(-1.62)
MKT_SHARE	-0.1260	-0.1249	-0.1212	-0.1276
	(-0.92)	(-0.91)	(-0.87)	(-0.93)
ZSCORE	-0.0127	-0.0125	-0.0129	-0.0127
	(-3.59)***	(-3.62)***	(-3.63)***	(-3.65)***
NOA	0.1155	0.1156	0.1139	0.1161
	(5.28)***	(5.31)***	(5.18)***	(5.36)***
CEO_AGE	-0.0467	-0.0511	-0.0488	-0.0477
	(-2.75)***	(-3.02)***	(-2.83)***	(-2.77)***
INSTOWN	0.2845	0.2907	0.2921	0.2901
	(2.24)**	(2.31)**	(2.29)**	(2.30)**
CEO_TENURE	-0.0161	-0.0143	-0.0166	-0.0154
	(-1.67)*	(-1.45)	(-1.70)*	(-1.57)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. obs.	24,549	24,549	24,549	24,549
Adjusted R^2	0.0638	0.0637	0.0636	0.0637

This table reports the results of an OLS regression examining the effect of CEO network size on *RAM* by using Alternative Network Measures for samples of 24,549 firm-years. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively, all two-tailed. *Betweenness* = how frequently the CEO lies on the shortest path between two other individuals in the network; *Closeness* = the number of indirect as well as direct connections; *Eigenvector* = how central are the individuals connected to the CEO; *rDegree* = the number of first-degree connections in the network relative to total network degree. See Liu (2014) for further details of these definitions. Appendix A defines the remaining variables.